In the Claims:

1. (Currently Amended) Apparatus for calculating numerical solutions for partial differential equations in successive intervals using adaptive dynamic meshes, comprising:

at least one neural network part for producing predictions of values of a parameter at a following interval based on values of said parameter available from previous intervals, and

a mesh adaptation part, associated with said at least one neural network part, configured for adapting a dynamic mesh over a domain of a respective partial differential equation using said predictions, such that said dynamic mesh adaptively refines itself about emerging regions of complexity as said partial differential equation progresses over said successive intervals.

2. (Original) Apparatus according to claim 1, wherein said successive intervals are time intervals.

3. (Original) Apparatus according to claim 1, wherein said parameter is a gradient.

4. (Currently Amended) Apparatus according to claim 1, wherein said dynamic mesh adaptation part is further configured to adaptively coarsen said dynamic mesh about regions of low complexity.

5. (Currently Amended) Apparatus according to claim 1, wherein said dynamic mesh adaptation part comprises a first thresholder for thresholding gradients from said at least one neural network parts, such that gradients above said threshold value are taken to indicate complexity and to lead to local refining of said dynamic mesh.

6. (Currently Amended) Apparatus according to claim 4, wherein said dynamic mesh adaptation part comprises a second thresholder for thresholding gradients from said at least one neural network parts, such that gradients below said threshold value are taken to indicate complexity and to lead to local coarsening of said dynamic mesh.

7. (Currently Amended) Apparatus according to claim 1, wherein said at least one neural network part comprises two neural networks, each having an input layer of input elements, at least one hidden layer of hidden elements and an output layer of at least one output element, said two neural networks differing from each other in respective numbers of input elements.

8. (Original) Apparatus according to claim 7, wherein each hidden element defines a hyperbolic tan-sigmoid transfer function.

9. (Original) Apparatus according to claim 7, wherein each output element defines a linear transfer function.

10. (Currently Amended) Apparatus according to claim 7, wherein a first of said neural networks is a boundary element neural network for calculating gradients of boundary elements of said adaptive dynamic mesh, and a second of said neural networks is an interior element neural network for calculating gradients of interior elements of said adaptive dynamic mesh.

11. (Original) Apparatus according to claim 10, wherein said boundary element neural network has fewer input elements than said interior element neural network.

12. (Original) Apparatus according to claim 7, wherein said input elements are connected to gather for a given mesh element a gradient of said mesh element, and a gradient of each neighboring element for each of a current and a previous interval.

13. (Currently Amended) Apparatus according to claim 12, wherein each hidden element defines a hyperbolic tan-sigmoid transfer function, each output element defines a linear transfer function, a first of said neural networks is a boundary element neural network for calculating gradients of boundary elements of said adaptive dynamic mesh, and a second of said neural networks is an interior element neural network for calculating gradients of interior elements of said adaptive dynamic mesh, and said boundary element neural network has fewer input elements than said interior element neural network.

14. (Original) Apparatus according to claim 13, wherein said interior element neural network comprises eight input elements, six hidden elements and one output element.

15. (Original) Apparatus according to claim 13, wherein said boundary element neural network comprises six input elements, six hidden elements and one output element.

16. (Currently Amended) Apparatus according to claim 1, wherein said at least one neural network part is trainable by using initial random interval calculations of a respective partial differential equation.

17. (Currently Amended) Apparatus according to claim 18, wherein said at least one neural network part is configured for training using the Levenberg Marguardt training method.

18. (Currently Amended) Method of adapting a finite element of a dynamic mesh interactively with calculations of numerical solutions for a partial differential equation in successive intervals, said partial differential equation being calculated over a domain in accordance with respective finite elements of said dynamic mesh, each successive interval using a further adaptation of said dynamic mesh, the method comprising:

producing predictions of values of a parameter of said partial differential equation at mesh elements at a following interval based on values of said parameter available from previous intervals, and

adapting said dynamic mesh over said domain of a respective partial differential equation using said predictions, such that said dynamic mesh adaptively refines itself about emerging regions of complexity as said partial differential equation progresses over said successive intervals.

19. (Original) The method of claim 18, wherein said parameter is a gradient.